Classification of Endoscopic Images Based on Texture and Neural Network

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Abstract

Computerized processing of medical images can ease the search of the representative features in the images. The endoscopic images possess rich information expressed by texture. Regions affected by diseases, such as ulcer or coli, may have different texture features. The texture model implemented in this study is Local Binary Pattern (LBP) and a log-likelihood-ratio, called the G-statistic, is used to evaluate the similarity of regions based on LBP. The neural network is used in the classification. SOM and BP are applied and compared. The texture model and classification algorithm are implemented and tested with clinically obtained colonoscopic data. For large amount of colonoscopic images, proper classification results corresponding with unique medical features can be acquired, which suggests that the unsupervised endoscopic image classification is applicable.

Keywords: texture, classification, neural network, endoscope

1. Introduction

Conventional diagnosis of endoscopic images employs visual interpretation by an expert physician. Since the beginning of computer technology, it becomes necessary for visual systems to "understand a scene", that is, making its own properties to be outstanding, by enclosing them in a general description of an analysed environment [1]. Computerized image comprehension of endoscopic images offers a powerful tool for enhancing images and rendering them easier for the physician to point out abnormality.

Texture features characterize the statistical or structural relationship between pixels, and provide measures of properties such as contrast, smoothness, coarseness, randomness, regularity, linearity, directionality, periodicity, and structural complexity. There was little work reported in the literature using texture information and it can indeed be very useful in clinical endoscopic diagnosis.

Artificial neural networks (ANN) have become popular over the last ten years for diverse applications on pattern recognition, image classification, medical diagnosis, control systems, etc [2]. The major advantage of neural network methods over classical statistical approaches is the relative insensitivity to selection of the training sets afforded by generalization. It makes artificial neural networks a strong candidate for diagnostic problems, where a set of symptoms is mapped to a set of possible diagnostic classes.

2. Methodology

The method is composed of two steps, namely, the extraction of texture features and classification using neural network.

2.1. Texture model for feature extraction

In recent research, many different approaches to unsupervised colour texture segmentation have been proposed. Different models are used such as Markov random field (MRF) models [3], orthogonal polynomial model [4], feature distributions [5] and hierarchical colour clustering [6]. Some texture measures based on feature distributions are compared by Timo Ojala, et al [7]. These measures are Grey-level difference method [8][9], Laws' texture

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Abstract

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measures [10], Centre-symmetric covariance measures and Local binary pattern. The local binary pattern (LBP) feature performs the lowest error rates for both the classification and pairs of complementary measures. Hence the LBP model is a proper selection for this project and it is implemented for the segmentation of colonoscopic image.

LBP describes the spatial structure of the local texture, but it does not address the contrast and intensity of the texture. A texture unit (TU) is represented by eight elements, in two-level version each of which has one of three possible values (0, 1) obtained from a neighbourhood of 3×3 pixels. The details are shown in figure 1.

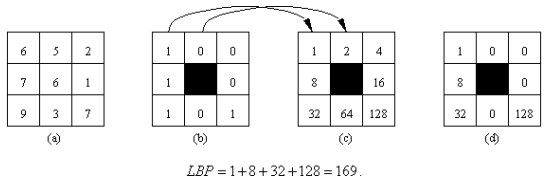

Fig. 1. Two-level version (LBP) of the texture unit.

In the research taken by T. Ojala, et al [5], it was proposed to combine LBP with a simple contrast measure C. It is also called complementary feature pairs. However through experimental results it was seen that combining LBP with the average intensity I generates more stable results for endoscopic images and hence the LBP/I model is implemented instead of LBP/C.

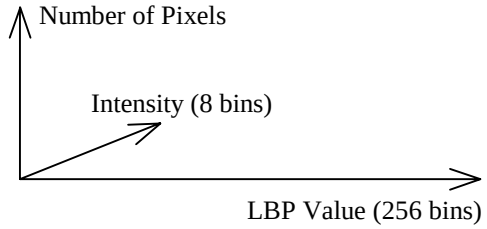

Fig. 2. LBP/I histogram

The LBP/I distribution is approximated by a discrete two-dimensional histogram as shown in Fig. 2., which was similar to what is proposed by T. Ojala, et al, [5]. The size of the histogram is $256\times b$, where b is the number of bins for I. Choosing b is a trade-off between the discriminative power and the stability of the texture transform. If b is too small, the histogram will lack resolution and consequently very little discriminative information will be added to the process. However, since the image region contains a finite number of pixels, it does not make sense to go to the other extreme for then the histogram becomes sparse and unstable. In this project the number of bins was chosen to be 8 bins.

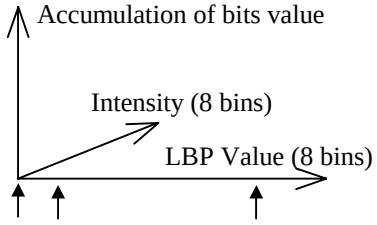

Fig. 3. Compact LBP/I histogram

For the relative high computation consuming of the LBP/I histogram, a alternative construction of the LBP/I histogram is proposed, which can be called Compact LBP/I histogram. Using the same example shown in Fig. 1., the Compact LBP/I histogram is shown in Fig. 3. Here the LBP keeps its original binary form and each of the 8 bits corresponds to one bin in the histogram. Hence the total number of bins of the LBP is also 8. This alternation minimizes the decrease of discrimination but the size of histogram is greatly reduced.

A log-likelihood-ratio, the G statistic [11] (Equation 1), which is a modification from Kullback's criterion, is used as a pseudo-metric for comparing LBP/I distributions. The value of the G statistic indicates the probability that the two sample distributions

come from the same population (higher the value lower the probability).

$$G=2\left(\left[\sum_{s,m}\sum_{i=1}^{n} f_i \log f_i\right]-\left[\sum_{s,m}\left(\sum_{i=1}^{n} f_i\right)\log\left(\sum_{i=1}^{n} f_i\right)\right]\right.$$
$$-\left[\sum_{i=1}^{n}\left(\sum_{s,m} f_i\right)\log\left(\sum_{s,m} f_i\right)\right]$$
$$\left.+\left[\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\log\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\right]\right) \quad (1)$$

where s, m are the two sample histograms, n is the number of bins and f_i is the frequency at bin i. Here n equals to the size of LBP histogram, $256\times b$ or $8\times b$.

If a image contains different features, a preliminary segmentation algorithm can be carried out, which involves hierarchical splitting, agglomerative merging and pixelwise classification. The image is then divided into several regions with the following classification procedure independently.

2.2. Classification using neural network

The Self-Organizing Map (SOM) is applied for the classification process. The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a one- or two- dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion [12]. It is generally held that the SOM is formed in an unsupervised process, which means there is no external teacher or critic to oversee the learning process. For the complexity of endoscopic images, sometimes it is difficult to determine that the individual regions belong to which class. It is also the convenience to apply the SOM for its unsupervised character.

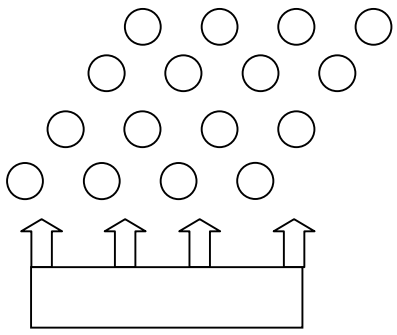

Fig. 4. The array of neurons in a two-dimensional SOM array.

Consider Fig. 4. The SOM here defines a mapping from the input data space R^n onto a two-dimensional array of nodes. Here R^n is defined upon the two-dimensional LBP histogram, hence n is $256\times b$. The lattice type of the array is defined to be rectangular. And the lattice size is set to 4×4 for current test. With every node i, a parametric reference vector

$$\mathbf{m}_i=[\mu_{i1},\mu_{i2},\cdots,\mu_{in}]^T\in R^n \quad (2)$$

is associated. The input vector connected to all neurons is

$$\mathbf{x}=[\xi_1,\xi_{2,}\cdots,\xi_n]^T\in R^n \quad (3)$$

Here $\xi_k, k=1,2\cdots n$, corresponds to every bins in the LBP histogram. It should be noted that the input vector $\mathbf{x}$ should be normalized upon the area of the corresponding region of endoscopic images.

In the competitive process of SOM, the G statistic is defined as distance measure. The subscript c of winning neuron $\mathbf{m}_c$ is defined as:

$$c=\arg\min_i\{G(\mathbf{x},\mathbf{m}_i)\} \quad (4)$$

The update equation is

$$\mathbf{m}_i(t+1)=\mathbf{m}_i(t)+h_{ci}(t)[\mathbf{x}(t)-\mathbf{m}_i(t)] \quad (5)$$

The neighborhood function $h_{ci}(t)$ can be written in terms of the Gaussian function,

$$h_{ci}(t)=\alpha(t)\cdot\exp\left(-\frac{\|r_c-r_i\|^2}{2\sigma^2(t)}\right) \quad (6)$$

Both $\alpha(t)$ and $\sigma(t)$ are some monotonically decreasing functions of time. r_c and r_i are

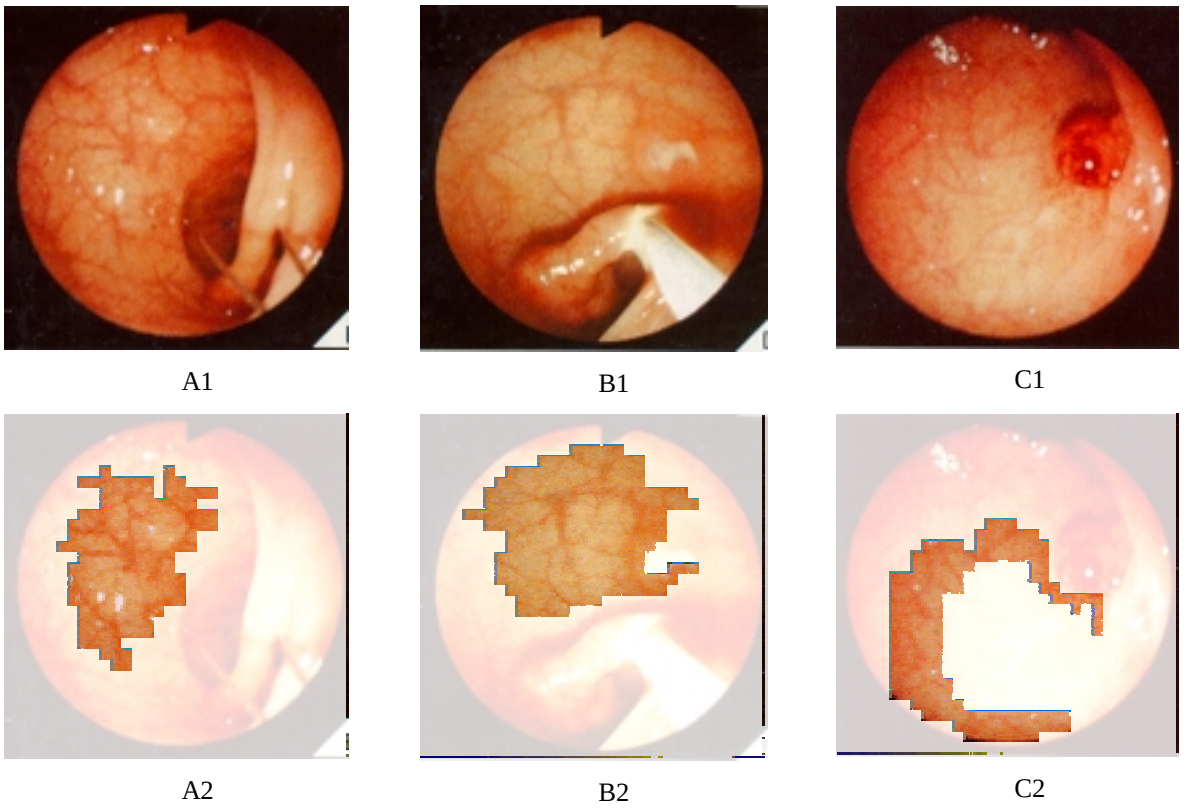

Fig. 5. Regions that correspond to same neuron in the SOM for colonoscopic images

the location vectors of nodes c and i, respectively, in the array.

3. Results and discussion

The texture model and image classification algorithm are implemented and tested with clinically obtained colonoscopic data as shown in Fig. 5. The first row contains the original images. Initially a segmentation algorithm is implemented and the three regions shown in the second row correspond to the same neuron in the SOM. And it is obvious that they are all the blood vessel regions, which can be regarded as a reasonable classification result. There are many medical features in the colonoscopic images that present prominent texture properties such as as ulcer or Melanosis coli. Hence proper classification results corresponding with unique medical features are expected to be obtained, which suggests that the unsupervised endoscopic image classification is applicable. The main advantages of the proposed method are the flexibility brought from neural network, stability brought from the texture method and the absence of any requirement of prior knowledge and the parameter values of the image to be processed.

4. Conclusion

A new method is developed for the classification of endoscopic images. The reasonably good results suggest its high potentiality to contribute to a totally intelligent auto-diagnosis endoscopy system.

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